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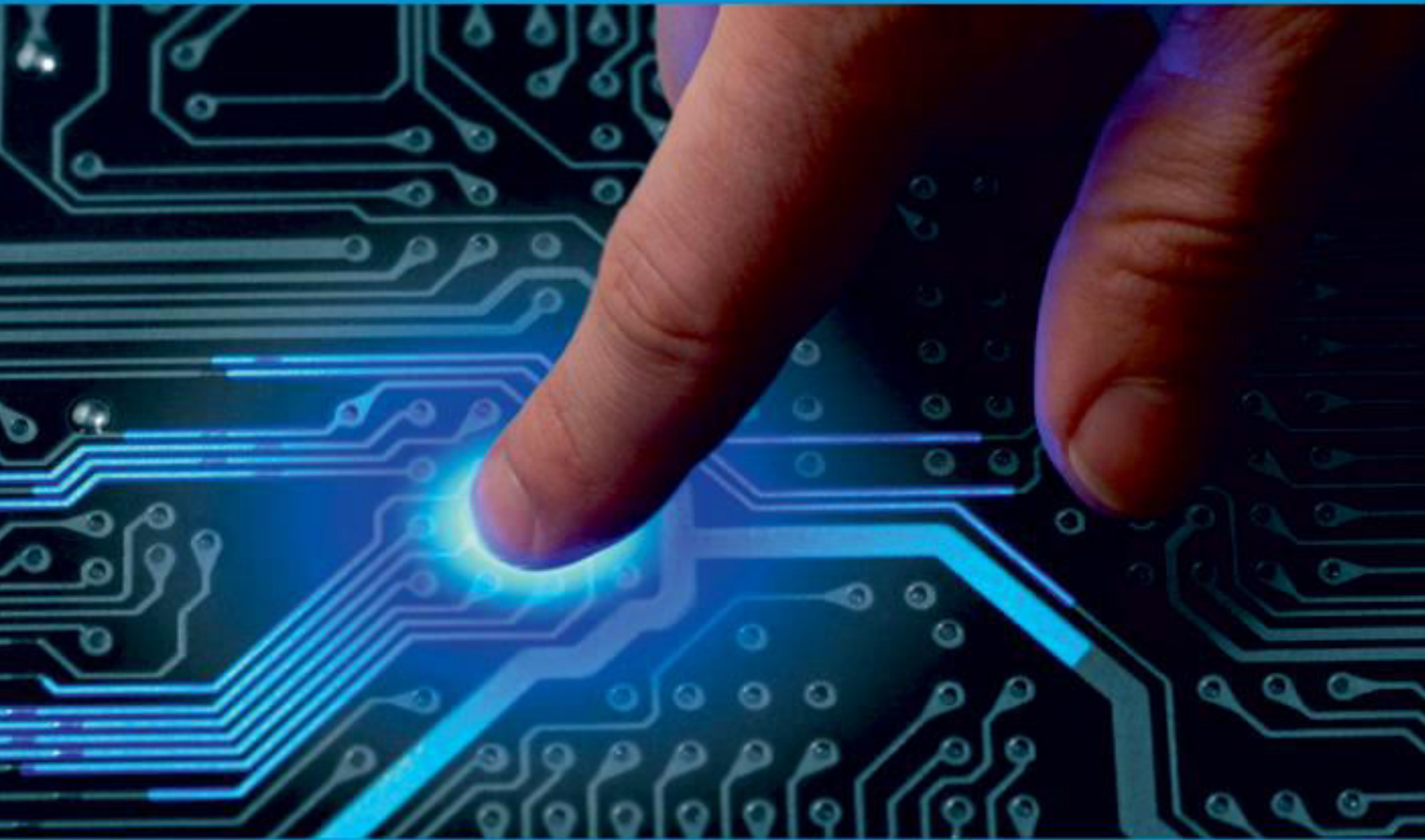

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Deep Learning Model to Predict Parkinson Disease

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ABSTRACT: Parkinson's disease is a tragedy for retirees because it causes the nervous framework to deteriorate and, as a consequence, the participant's maneuverability. The application's precise involvement in Parkinson's disease significantly increases the chances of preventing it from worsening. The framework can circumvent this by gathering exact data from the individual or by supplying certain sample handwritten patterns, such as spirals or waves. This review article looked at a collection of appropriate publications as a solution. The research demonstrates that the computer vision architecture is the final answer for revealing the Parkinson disease probability by studying the sufferer's hand-drawn image. So to enhance the model of Parkinson's detection processa neural network model is constructed using the Convolutional neural network for both types of patient sketches including the Spiral and wave.After explanatory detailing the model is successfully deployed the Parkinson's Disease detection and the result are evaluated for the Root mean square error rate. The obtained results showthe system yields great RMSE for the detection of the Parkinson's disease for the hand written sketch by the patient.

KEYWORDS: CNN, Decision Making, Parkinson's disease Detection.

I. INTRODUCTION

The phenomena of modernization, as well as subsequent improvements in the medical sector, have culminated in a vastly enhanced standard of living for the average human. Biomedical progress has also contributed to the overall incremental improvement in human longevity. This has been a boon to society as a whole, because individuals can now survive much extended, happier, and pain-free lives. This appears to have undermined the well-being of the rapidly increasing demographic of senior citizens. These folks are suffering with challenges that were not as common when the expected lifetime was much shorter. Several older residents suffer from extremely rare illnesses that are exclusively present in the aging population.

Parkinson's disease is a well-known ailment. It is a persistent neurological condition that is steadily increasing in prevalence amongst some of the elderly. This illness is marked by a drop in dopaminergic concentration in the body, a neurotransmitter which actively encourages interaction and cooperation. Reduced stability and the onset of uncontrollable muscle convulsions are symptoms of dopaminergic insufficiency. This is extremely inconvenient, and it may increase the elderly patient's risk of incidents and injury. A failure in the cortex central nervous system, particularly the ganglia area, is the most common cause of dopamine insufficiency, which impairs comprehension.

Parkinson's disease is a cortex deteriorating illness that affect the wellbeing of countless of retirees throughout the globe. Due to the obvious variability of Parkinson's disease, manifestations might proceed independently from one individual to the next. Individuals with Parkinson's disease may have convulsions, which occur mostly during rest. Shaking in the hands, muscular stiffness, and mobility and equilibrium issues are all possibilities. Parkinson's disease indicators may be divided into two categories: movement-related or motor functions and non-movement-related or non-motor complaints. Individuals with non-symptoms are actually significantly impacted than those with movement disorders. Anxiety, sleep behavior abnormalities, impairment of odor, and cognitive decline are examples of non-motor manifestations.

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Since there are no true guidelines for assessing the neurodegeneration, diagnosing Parkinson's disease is very difficult. Parkinson's disease, on the other hand, can be identified using a range of behavioral and diagnostic characteristics. The freezing gait evaluation and speech synthesis tests are among the techniques that deal with mobility and involuntary movements. The doctors also employ a spiral approach to look for recurrent spasms, which show up as a jagged line inside the spirals. On some of these types of tests, medical specialists perform extensive manual calculations. This type of evaluation takes a long time and requires a lot of work from the experts. Qualitative categorization also bears the risk of introducing human error into an otherwise possibly fatal prediction. As a consequence, there is a need for a methodology that can be used to evaluate and diagnose Parkinson's disease utilizing computer image and machine intelligence approaches.

There seems to be a set of different classifiers that have already been discovered as producing the best and most reliable evaluation of Parkinson's disease in an individual. As input data, the spiral-containing photographs are delivered into the software. The Region of Interest approach is used to isolate the important part of a photograph that will be used for recognition. The region of interest is one of the most prominent methods for identifying the related region that is necessary for an appropriate inspection of the approach. This is used in conjunction with Convolutional Neural Networks and Decision Making technologies to boost the effectiveness of Parkinson's disease identification techniques, which will then be detailed in future research publications.

Related work is allocated in the section 2 of this research paper. Whereas section 3 elaborates the proposed work and obtained results are discussed in section 4. In the end of this research paper future works are discussed in brief along with the conclusion.

II. RELATED WORKS

S. K. Khare et al. [1] demonstrate an automated, accurate, and resilient PDCNNet model depending on EEG signals The EEG waves are utilized to generate the SPWVD graphs. Using two open-source EEG datasets, the SPWVD plots in conjunction with CNN produced the best PD detection performance. Using two PD benchmark datasets, the suggested technique has an accuracy of 99.73 percent, 100 percent, and 99.93 percent in automatically recognizing PDSF, PDSO, and PD classes. By decreasing the cross-term interference of time and frequency, the SPWVD can extract more representative and hidden information. The SPWVD plots aid in capturing spatial and temporal features at the same time, making it extremely distinct in distinguishing PD and HC participants. The presented prototype is portable and may be utilized in real-time Parkinson's disease diagnosis utilizing EEG data.

M. Rumman et al. introduced a framework that approached the problem of identifying PD from a different perspective than previous methods. DaTSPECT pictures were processed in this research to detect the putamen and caudate region, which is the region of interest (ROI) for this investigation, and the area of these sections was discovered. Subjects with Parkinson's disease have smaller putamen and caudate area than those who do not have Parkinson's disease [2]. An artificial neural network (ANN) was utilized to classify Parkinson's disease and healthy control. When placed in an unknown comparable setting with previously supplied knowledge, ANN has a remarkable capacity to discern patterns and extract meaning from those patterns. The discovered results are quite relevant to real-life scenarios. A model with more datasets can provide even more consistent accuracy. More data may be used to train the ANN, making it more efficient in categorization.

K. H. Leung et al. present a deep-learning-based strategy that included both imaging and non-imaging clinical variables and has shown substantial promise for predicting prognosis in Parkinson's disease patients. This study examined longitudinal clinical data from 198 Parkinson's disease patients, including DAT-SPECT pictures and clinical assessments. The DAT-SPECT pictures were preprocessed by choosing a continuous segment of 21 image slices from each image with the greatest relative intensity in the transaxial direction as the center slice [3]. The photos were then zero-padded, yielding 128×128 x 21 images for both years 0 and 1. Given the availability of a heterogeneous longitudinal dataset, the authors created numerous deep-learning-depend algorithms with varying input data. The first technique exclusively makes use of data from DAT-SPECT pictures. The second technique exclusively employs data from non-imaging clinical characteristics. Finally, both imaging and non-imaging methods are provided for the final technique.

A new design for deep neural networks GS-RNN is introduced by K. Hu et al. that processes spatial-temporal data in the form of dynamic graph sequences. The basic elements of GS-RNNs are graph RNN cells and vertex-wise RNN

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cells, which simulate both structural and temporal graph patterns concurrently. GS-RNNs may be utilized to construct vision-depend FoG findings as a fine-grained sequential modeling job in this case [4]. Extensive experimental findings on an in-house dataset, which contains the highest number of patients in the literature of video-based PD gait analysis, show that the suggested GSRNN designs outperform the competition. Furthermore, by localizing the important vertices of a FoG film, the graph representation of anatomic joints gives an understandable interpretation of the detection findings, which is useful for clinical evaluations in practice.

Depending on DCGAN, SN, and feature matching, a Spectrogram Deep Convolutional Generative Adversarial Network (S-DCGAN) was presented by Z. -J. Xu et al. The model is utilized to recognize voiceprints. This model can create high-resolution spectrograms for sample augmentation by better capturing the spectrogram's textural properties. The addition of the SN technique enhances training stability when compared to DCGAN [5]. The feature matching approach increases the image quality and, in the end, produces a high-resolution spectrogram. The experimental results reveal that voiceprint recognition accuracy improves in a small sample of PD patients, and it is better than some of the most advanced technologies.

To categorize MRI patches of Parkinson's disease and healthy patterns, P. M. Shah et al. developed a bespoke CAD-based CNN design. The introduced network with three convolutional layers efficiently learns patterns from training samples of the benchmark PPMI dataset, resulting in enhanced accuracy. The findings demonstrate that the introduced network is capable of autonomously learning correct Parkinson's disease traits. During the testing, the authors discovered that the little dataset was a key issue, causing the CNN model to overfit [6]. They were able to overcome the overfitting problem by using suitable network architecture and dropout layers.

Y. Zhang et al. [7] offer an approach for developing high-accuracy and low-latency FoG prediction models depending on impaired gait patterns. The authors expected that step-to-step impaired gait parameters such as cadence, symmetry, and variability are more relevant in FoG prediction than traditional FoG detection features and need shorter segmentation windows. Therefore, utilizing the compromised gait parameters, the authors were able to anticipate the imminent FoG with greater accuracy and reduced latency. They also anticipated that the duration of individualized pre-FoG phases was positively connected with illness conditions, which they utilize as the foundation for an FoG prediction model that is more accurate than unified labeling.

Depending on premotor indicators (i.e., Rapid Eye Movement (REM), sleep Behaviour Disorder (RBD), and olfactory loss) W. Wang et al. suggested a deep learning model to automatically differentiate normal persons and patients afflicted by PD [8]. The suggested deep learning model demonstrated strong detection capability, with an accuracy of 96.45 percent. This is mostly owing to the deep learning model's favorable capabilities in learning linear and nonlinear features from PD data without the requirement for hand-crafted feature extraction. The results reveal that the developed deep learning model outperforms the twelve examined machine learning models in distinguishing normal persons from Parkinson's disease patients.

Using EEG data acquired from individuals with Parkinson's disease and FOG, Z. Cao et al. explored the brain dynamics of FOG and intentional pausing events. The experimental outcome showed that FOG episodes were related to aberrant EEG dynamics and that intentional halting could be distinguished from FOG events. The data reveal that freezing episodes are linked with considerably enhanced theta and alpha band power throughout the central and occipital regions when the transition to the freezing phase is compared to the freezing period itself. Furthermore, when compared to the FOG period, the EEG power reduced dramatically during the voluntary halting interval [9]. Their findings shed new light on the fast transition dynamics that underpin the phenomena of FOG and may pave the way for therapeutic prediction and mitigation of freezing episodes in sensitive patients.

L. Zahid et al. present the Alexnet model for deep feature extraction and finding of PD which provided a basic acoustic features-based strategy and also explored a pre-trained convolution neural network architecture. The authors employed transfer learning-based categorization for a fair comparison [10]. The suggested approaches are evaluated using Parkinson's disease speech recordings from the PC-GITA dataset. The outcome suggests that the strategy depends on deep characteristics yielded superior outcomes.

CNN and CNN-BLSTM are two deep learning-based learning models suggested by C. Taleb et al. for end-to-end time series categorization. To cipher time series into pictures for the CNN framework, two distinct frameworks were proposed: Gramian angular field images and spectrogram images. The benefit of employing spectrogram pictures is

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that they compute local short-term information that occurs in non-stationary online handwritten signals before normalization, whereas the other two algorithms normalize the time series into a fixed dimension image without extracting local information [11]. The fresh time series are utilized directly by the CNN-BLSTM framework, with no need to transform them into pictures. This method has been tested to confirm the relevance of taking into account local information before integrating on a temporal scale.

A. H. Neehal et al. developed a novel technique by evaluating resting-state fMRI image data. Each voxel represents a time series data point that is utilized to calculate in the time-frequency domain [12]. STFT is employed in this method to obtain the signal's localized frequency information. The output of the STFT function yields a frequency vector and a time vector, which are then utilized to categories the data using the SVM classifier. The SVM classifier predicted the early phases with the highest accuracy. The authors were able to execute feature extraction for the targeted objective of recognizing early stages of PD since they used data from early-stage PD patients.

A. S. Alharthi et al. show how to utilize a deep convolutional neural network (DCNN) to analyze GRF data from Parkinson's patients. This extends the author's prior work which was confined to a DCNN's classification performance on GRF data using LSTM and statistical analysis. The idea is that they may use spatiotemporal gait GRF signals to categorize individuals as healthy or PD patients, and relate key known events in the gait cycle to cognitive decline owing to PD severity [13]. To their knowledge, this is the first time the LRP method has been utilized to analyze spatiotemporal gait GRF data in Parkinson's disease. They also use perturbation noise and LRP relevance scores to validate the approaches for how successful the obtained classification result is.

III. PROPOSED WORK

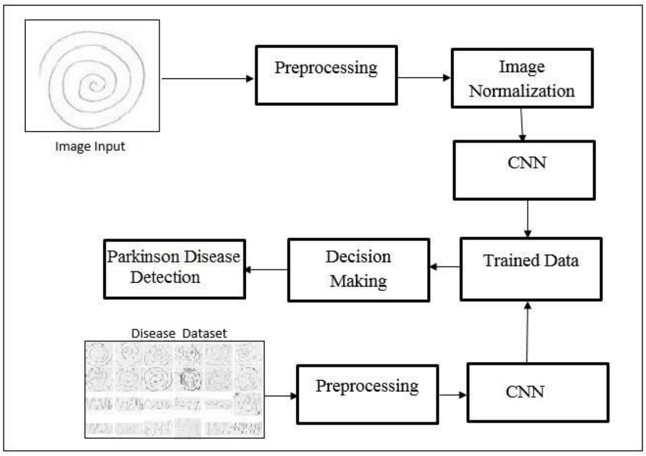

Figure 1: Proposed work For Parkinson's Disease Detection

The Proposed work for the Parkinson's disease detection is depicted in the above figure 1. The steps that are considered for the deployment of the Parkinson Disease detection is explained with the below mentioned steps.

Step 1: Dataset Collection and Preprocessing – This is the initial step of the proposed model. To deploy the model a handwritten drawing for spiral and wave curves sketches by the patients withParkinson's disease and healthy persons is downloaded from the URL : https://www.kaggle.com/kmader/parkinsons-drawings?. Then obtained images from the dataset are rescaled using the python programming language. For this purpose PIL library is used to rescale the wave images to the dimension of 170 X 170. And Spiral images into the dimension of 150 X 150.

*Step 2: Training the dataset images using the Convolution neural network:*To train the dataset images which are classified into the train and test data for both spiral and Wave image respectively. Spiral images contain 866 train images and 399 Test images respectively. On the other hand Wave images contain 464 train images and 288 test images respectively.

At the beginning of the training the data through convolutional neural network libraries from the keras and tensorflow are installed and imported. After this a ratio of 1:255 is set to learn the pixel in-depth to form an object for

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Image data generator for both the training and testing data. Then a batch size is set to 32 for wave and 64 for Spiral images respectively.“Grayscale“color mode is set to form “categorical“class mode.

After Finishing this initial process asequential neural network model is set to create its object. A convolution layer is added as the first layer of the neural network with 32 kernels of size 3 X 3 with “ Relu” activation Function. This is done with the respective input image shape for wave and spiral images. A color channel of one is set to finish the first layer of the Convolution neural network. For the second layer of the convolution neural network 64 Kernels of size 3 X 3 are used with “Relu” activation function. Following this a max pooling 2D layer is added with kernel Size 2 X2. A dropout of 25% is engaged using the Droput function.

Third and Fourth Layers are added with 128 kernels of Size 3 X3 following with ‘Relu” Activation function. Following each of the layers a maxpooling 2D layer is added with kernel size 2 X 2. Then again a dropout layer with 25% is added in the end.

Once the Neural network has flatten then the tensors are collected with 1024 size and activation function “Relu”.At the end of the model a dropout layer of 50% is applied to collect the trained data in two classes like “healthy” and “Parkinson” by applying “ Softmax” Activation function.

The neural network architecture used for Convolution is depicted in figure 2 below.

Layer	Activation
CONV 2D 32 X 3 X 3	Relu
CONV 2D 64 X 3 X 3	Relu
MaxPooling2D 2 X 2	
Dropout 0.25	
CONV 2D 128 X 3 X 3	Relu
MaxPooling2D 2 X 2	
CONV 2D 128 X 3 X 3	Relu
MaxPooling2D 2 X 2	
Dropout 0.25	
Flatten	
Dense 1024	Relu
Dropout 0.25	
Dense 2	Softmax
Adam Optimizer	

Figure 2: Architecture of the Convolution Neural Network

The designed neural network model is then optimized using the “ Adam” Optimizer to run the model for 800 epochs for spiral and 500 for wave Patterns. The obtained data is stored in an .h5 format of file for the future use during the testing.

Step 3: Testing through Decision making- Here in this step once the test image is fed to the system, then the system initially checks for their respective dimension. Based on the dimension the respective Pre trained spiral and Wave models are invoked to predict the disease. In this process again the neural network is built along with the trained data stored in the .h5 file.This Neural network is subject to predict the class of healthy or Parkinson ’s diseasefor the fed testing image.

IV RESULTS AND DISCUSSIONS

The presented approach for Parkinson’s disease identification is developed on a machine running on a Windows Operating System and is coded in python programming language. The Spyder IDE is being used for the purpose of coding the proposed approach. The laptop used for the implementation consists of a configuration of Intel Core i5 as processor with 1TB hard drive and 8GB of RAM.

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The detailed assessment of the Parkinson Disease identification technique needs to be performed for the understanding if the implementation of the Convolution neural Network can be performed effectively. The presented approach uses an image of spirals and sine waves sketched by the subject as input. The RMSE performance metric is successfully used to evaluate the functionality of the Parkinson Disease Identification. The experimental examination is covered in the following section.

Performance Evaluation through Root Mean Square Error

The Root Mean Square Error (RMSE) is calculated to determine the margin of error of the proposed approach. The RMSE is utilized in this investigation to calculate the error margin seen between actual Parkinson Disease Detection and the Estimated Parkinson Disease Detection via the CNN component. The RMSE technique is depicted in equation 1 below.

$$\mathrm{RMSE}_{fo} = [\sum_{i=1}^{N} (z_{f_i} - z_{o_i})^2 / N]^{1/2}$$

Where
$\sum$ - Summation.
$(Z_{fi} - Z_{oi})^2$ - Differences Squared for the Parkinson Disease identification.
N - Number of Images.

The Mean Square Error needs to be measured initially before the evaluation of the Root Mean Square Error which is measured effectively. The Measurement of the Mean Square error is done between the identified Parkinson's disease and the actual Parkinson's disease. This approach is subjected to a number of executions with varying number of input drawings to determine the error achieved. The experimental findings have been stipulated in the table 1 given below.

Table 1: Mean Square Error Measurement

Experiment No.	No. of Actual Parkinson's Disease Identification	No. of Achieved Parkinson's Disease Identification	MSE
1	6	5	1
2	7	7	0
3	9	9	0
4	10	10	0
5	11	10	1
		RMSE	0.632

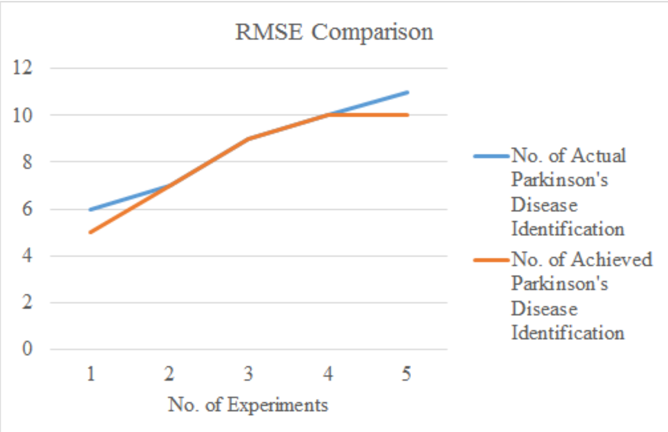

Figure 2: No of Expected Identifications V/s No of Obtained Identifications

The outcomes tabulated in the table 1 above are being utilized for the purpose of graphical representation in the line graph given in the figure 2 above. The evaluation of the error has been performed to determine the accuracy of the Convolutional Neural Network in the detection of the Parkinson's disease. The Average Mean Square Error attained by the approach is then transformed in to the Root Mean Square error by taking the square root. The RMSE measured is achieved as 0.632 which is quite low and specifies the accurate implementation of the Convolutional Neural Network component. The proper execution of the CNN approach has considerably improved the performance of the Parkinson's disease identification considerably.

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V. CONCLUSION AND FUTURESCOPE

Parkinson's disease is one of the most disabling neurodegenerative conditions. There is no recognized cause for the onset of this illness that is commonly seen in the elderly. The illness is related to cognitive impairment and a change in the physicochemical properties of both the brain's neurons. The disorder is seldom recognized in its initial phases since the symptoms are modest and infrequent, rendering it difficult to detect and assess. As a consequence, the goal of this study is to develop a suitable method for identifying Parkinson's disease in patients that could be used to make an accurate assessment on their own. To give a benchmark analysis of the approache for Parkinson's disease identification, this researchpaid attention to trainthe images using the Convolution neural netwotk. This has being observed that the majority of the techniques include flaws. Convolutional Neural Network as well as Decision Making are therefore appropriate candidates for neural networks. The results of Root mean square error proves that the model incorporates the proper technique of deep learning for the evaluation of Parkinson’s disease detection.

For the future research this project can extends to work in mobile application as well as they can be enhanced work on readymade API

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